Does Adaptation to Climate Change Provide Food Security?

A Micro-Perspective from Ethiopia

Does Adaptation to Climate Change Provide Food Security? A Micro-Perspective From Ethiopia

Salvatore Di Falco, Marcella Veronesi, and Mahmud Yesuf

We examine the driving forces behind farm households' decisions to adapt to climate change, and the impact of adaptation on farm households' food productivity. We estimate a simultaneous equations model with endogenous switching to account for the heterogeneity in the decision to adapt or not, and for unobservable characteristics of farmers and their farm. Access to credit, extension and information are found to be the main drivers behind adaptation. We find that adaptation *increases* food productivity, that the farm households that did not adapt would benefit the most from adaptation.

Key words: adaptation, climate change, endogenous switching, Ethiopia, food security, productivity, spatial data.

JEL classification: Q18, Q54.

At the core of the ongoing debate regarding the implications of climate change in sub-Saharan Africa, there is the issue of food security. In this part of Africa, millions of small-scale subsistence farmers, generally with less than one hectare of land, produce food crops in extremely challenging conditions. The production environment is characterized by a joint combination of low land productivity and harsh weather conditions (e.g., high average temperature, scarce and erratic rainfall). These result in very low yields and food insecurity (Di Falco and Chavas 2009).

Food security is a broad concept. It encapsulates availability, access, and utilization of foodstuff.[1] In this paper we focus on one of the most important determinants of food availability in the Ethiopian subsistence farms context: food productivity (FAO 2002). The availability (and to some extent the access) of food is crucially determined by the productivity of these farm households. They account for about 95% of the national agricultural output, of which about 75% is consumed at the household level (World Bank 2006). With low diversified economies and reliance on rainfed agriculture, sub-Saharan Africa's development prospects have been closely associated with climate. For instance, the World Bank (2006) reported that catastrophic hydrological events such as droughts and floods have reduced Ethiopia's economic growth by more than a third.

Climate change is projected to further reduce agricultural productivity (Cline 2007; Parry et al. 2005; Rosenzweig and Parry 1994). A plethora of climate models converge in forecasting scenarios of increased temperatures for most of this area (Dinar et al. 2008). The fourth Intergovernmental Panel on Climate Change (IPCC) states that at lower latitude, in tropical dry areas, crop productivity is expected

Salvatore Di Falco is a lecturer (UK equivalent for assistant professor) at the London School of Economics; Marcella Veronesi is a researcher and lecturer at ETH Zurich, Institute for Environmental Decisions; Mahmud Yesuf is research assistant professor at Kansas State University.

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[1] For a critical discussion of the different dimensions and metrics of food security please refer to Barrett (2010), Gregory, Ingram, and Brklacich (2005), and Jenkins and Scanlan (2001).

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to decrease “for even small local temperature increases (1–2 °C)” (IPCC 2007, p. 11). In many African countries, access to food will be severely affected: “Yields from rain fed agriculture could be reduced by up to 50% by 2020” (IPCC 2007, p. 13). Given these discouraging prospects, it is no surprise that the identification of both “climate-proofing” technologies and adaptation strategies are vital to support the yields of food crops. These strategies can indeed buffer against climate change and play a crucial role in reducing the food insecurity of farm households.

This paper aims to contribute to the literature on climate change on agriculture by providing a micro perspective on the issue of adaptation and food security. We investigate how farm households’ decision to adapt, that is to implement a set of strategies (e.g., changing crop varieties, adoption of soil and water conservation strategies) in response to long run changes in key climatic variables such as temperature and rainfall, affects food crop productivity in Ethiopia. This seems particularly relevant because most of the debate on climate change in agriculture has been focusing on the impact of climate change rather than on the role of adaptation.

The links between climate change and food productivity have largely been explored focusing on the relation between climate variables and agriculture. There is, indeed, a large and growing body of literature that uses either agronomic models or *Ricardian* analysis to investigate the magnitude of these impacts (e.g., Deressa and Hassan 2010; Kurukulasuriya and Rosenthal 2003; Seo and Mendelsohn 2008). Agronomic models attempt to estimate directly, through crop models, the impacts of climate change on crop yields. They rely on experimental findings that indicate changes in yield of staple food crops (i.e., wheat) as a consequence of warming temperatures (e.g., Amthor 2001; Fuhrer 2003; Gregory et al. 1999). Then, the results from the model are fed into behavioral models that simulate the impact of different agronomic practices on farm income or welfare.

The *Ricardian* approach (pioneered by Mendelsohn et al. 1994) purports to isolate, through econometric analysis of cross-sectional data, the effects of climate on farm income and land value, after controlling for other relevant explanatory variables (e.g., factor endowment, proximity to markets). The *Ricardian* approach implicitly incorporates the possibility of the implementation of adaptation strategies by farmers.[2] Since it is assumed that farmers have been adapting optimally to climate in the past, the regression coefficients are estimating the marginal impacts on outputs of future temperature or rainfall changes already incorporating farmers’ adaptive response. Thus, adaptation choices do not need to be modeled explicitly. They have been efficiently implemented. One of the obvious shortcomings of this approach is that it is a “black box” that fails to identify the key adaptation strategies that reduce the implication of climate on food production.

Disentangling the productive implications of adaptation to climate change is of paramount importance. Besides determining the impact of climatic variables on food productivity, it is necessary to understand how the set of strategies implemented in the field by the farmers (e.g., changing crops, adopting water harvesting technologies or, soil conservation measures) in response to long term changes in environmental conditions affects crop productivity. More specifically, it is necessary to assess whether the farm households that actually did implement those adaptation strategies are indeed getting benefits in terms of an increase in the productivity of food crop. This is central if adaptation strategies need to be put in place.

As mentioned earlier, our focus on the productivity of food crops (and not on land values) is motivated by its implications for the achievement of food security. Moreover, using productivity seems particularly appropriate in the Ethiopian context. A key assumption of the *Ricardian* approach is that land markets are working properly.[3] Under this circumstance land prices will reflect the present discounted value of land rents into the infinite future (Deschenes and Greenstone 2007). Properly working land markets, however, may not be operating in areas of the developing world where land property rights are not perfectly assigned. This is the case of Ethiopia. In this country in 1975 a land reform was implemented. As result all land was made state property, land rentals as well as labor hiring were made illegal under the regime of Derg (1974 – 1991). After the change in the government land rentals and labor hiring were

[2] The *Ricardian* approach has been recently widely adopted in a series of country level analyses (see Dinar et al. 2008; Mendelsohn 2000). Global scale analysis can, however, mask tremendous local differences.

[3] An alternative approach would be to use farm net revenues (i.e., Deressa and Hassan 2010).

legalized. However, the predominance of oral contracts and agreements has prevented the formation of well-defined property rights, and large areas of this country are still plagued by tenure insecurity. Recent land certification reforms, in some areas, seem to be contributing to more secure tenure and the enhancement of land markets (Deininger et al. 2007; Holden et al. 2007).

There is existing literature on the estimation of the impact of climate change on food production at country, regional, and global scale (McCarthy et al. 2001; Parry et al. 2004; Pearce et al. 1996; Stern 2007). Insights from these studies are crucial in appreciating the extent of the problem and designing appropriate mitigation strategies at global or regional level. The aggregate nature of these studies, however, makes it very difficult to provide insights in terms of effective adaptation strategies at micro or farm household level.[4] Micro evidence on the impact of rainfall, temperature, and climate related adaptation strategies on crop yield is very scanty.

Our study tries to fill the gap in the literature by examining how the decision to adapt or not to adapt to climate change affects agricultural productivity in the Nile Basin of Ethiopia. We have access to a particularly rich database, which contains both farm households that did and did not adapt plus a very large set of control variables. Lack of enough spatial variation on key climatic variables (rainfall and temperature) in cross sectional data is one major issue to conduct micro level studies on climate change. This can be particularly true in developing countries where one meteorological station is set to cover a wide geographic area. To address this issue we employ household specific rainfall and temperature data generated by the *Thin Plate Spline* method of spatial interpolation. This method imputes the farm specific values using latitude, longitude, and elevation information of each farm household (see Wahba 1990 for details).

We take into account that the differences in food productivity between those farm households that did and those that did not adapt to climate change could be due to unobserved heterogeneity. Indeed, not distinguishing between the casual effect of climate change adaptation and the effect of unobserved heterogeneity could lead to misleading policy implications. We account for the endogeneity of the adaptation decision by estimating a simultaneous equations model with endogenous switching by full information maximum likelihood estimation. For the model to be identified, we use as selection instruments the variables related to the information sources (e.g., government extension, farmer-to-farmer extension, information from radio and neighborhood).

Finally, we build a counterfactual analysis, and compare the expected food productivity under the actual and counterfactual cases that the farm household adapted or not to climate change. Treatment and heterogeneity effects are calculated to understand the differences in food productivity between farm households that adapted and those that did not adapt, and to anticipate the potential effects of changes in agricultural policy. To our knowledge, considering the existing literature, this is a novel exercise.

We find that there are significant and non-negligible differences in food productivity between the farm households that adapted and those that did not adapt to climate change. We also find that adaptation to climate change increases food productivity. The impact of adaptation on productivity is smaller for the farm households that actually did adapt than for the farm households that did not adapt in the counterfactual case that they adapted. In addition, if the nonadapters adapted, they would produce the same as the adapters.

We control for the role of both rainfall and temperature. We follow the existing literature and include nonlinear terms for both these variables (Mendelsohn et al. 1994). We find that the estimated coefficients for rainfall in the main rain season (*Meher*) are statistically significant only for the group of farm households that did not adapt. The same variables display estimated coefficients that are not statistically significant when we consider only the group of farm households that implemented adaptation strategies. This may indicate that this group of farm households, through adaptation, is less reliant on the rainfall in the *Meher* season.

We also analyzed the drivers behind adaptation. Econometric results show that information on both farming practices (irrespective of its source) and climate change is crucial in affecting the probability of adaptation. In addition, we find that farm

[4] To the best of our knowledge, Temesgen (2006) is the only economic study that attempts to measure the impact of climate change on farm profit. This study applies the *Ricardian* approach where the cost of climate variability is imputed from capitalized land value. However, this study was conducted using subregional (agro-ecology) agricultural data, not farm household level data.

households with access to credit are more likely to undertake strategies to tackle climate change.

Description of the Study Sites and Survey Instruments

Ethiopia is a very interesting case study. A recent mapping on vulnerability and poverty in Africa listed Ethiopia as one of the countries most vulnerable to climate change with the least capacity to respond (Orindi et al. 2006; Stige et al. 2006). The country's economy heavily relies upon the agricultural sector, which is mostly rainfed. The agricultural sector accounts for about 40% of national GDP, 90% of exports, and 85% of employment. Ethiopia's vulnerability is indeed largely due to climatic conditions. This has been demonstrated by the devastating effects of various prolonged droughts in the twentieth century and recent flooding. The productive performance of the agricultural sector has been very low. For instance, agricultural GDP and per capita cereal production has been falling over the last forty years with cereal yield stagnant at about 1.2 tons per hectare. Direct implication is that large areas of Ethiopia are plagued by food insecurity.

This study relies on a survey conducted on 1,000 farm households located within the Nile Basin of Ethiopia in 2005. The sampling frame considered traditional typology of agro-ecological zones in the country (namely, *Dega, Woina Dega, Kolla* and *Berha*), percentage of cultivated land, degree of irrigation activity, average annual rainfall, rainfall variability, and vulnerability (number of food aid dependent population). The sampling frame selected the *woredas* (an administrative division equivalent to a district) in such a way that each class in the sample matched to the proportions for each class in the entire Nile basin. The procedure resulted in the inclusion of twenty *woredas*. Random sampling was then used in selecting fifty households from each *woreda*.

One of the survey instruments was in particular designed to capture farmers' perceptions and understanding on climate change, and their approaches on adaptation. Questions were included to investigate whether farmers have noticed changes in mean temperature and rainfall over the last two decades, and reasons for observed changes. About 90% of the sample perceived long term changes in mean temperature or/and rainfall over the last twenty years. About 68%, 4%, and 28% perceived mean temperature as increasing, decreasing and remaining the same over the last twenty years, respectively. Similarly, 18%, 62%, and 20% perceived mean annual rainfall increasing, declining, and remaining the same over the last twenty years, respectively. Overall, increased temperature and declining rainfall are the predominant perceptions in our study sites.

Furthermore, some questions investigated whether farm households made some adjustments in their farming in response to long term changes in mean temperature and rainfall by adopting some particular strategies. We define the undertaken strategies as "adaptation strategies," and create the dummy variable *adaptation* equal to 1 if a farm household adopted any strategy in response to long-term changes in mean temperature and rainfall, 0 otherwise. Changing crop varieties, adoption of soil and water conservation strategies, and tree planting were major forms of adaptation strategies followed by the farm households in our study sites. These adaptation strategies are mainly yield-related and account for more than 95% of the adaptation strategies followed by the farm households who actually undertook an adaptation strategy. The remaining adaptation strategies accounting for less than 5% were water harvesting, irrigation, non–yield related strategies such as migration, and shift in farming practice from crop production to livestock herding or other sectors. About 58% and 42% of the farm households had taken no adaptation strategies in response to long term shifts in temperature and rainfall, respectively. More than 90% of the respondents who took no adaptation strategy indicated lack of information, land, money, and shortages of labor, as major reasons for not undertaking any adaptation strategy. Lack of information is cited as the predominant reason by 40–50% of the households.

In addition, detailed production data were collected at different production stages (i.e., land preparation, planting, weeding, harvesting, and post harvest processing). The area is almost totally rainfed. Only 0.6% of the households are using irrigation water to grow their crops. Production input and output data were collected for two cropping seasons, i.e., *Meher* (long rainy season), and *Belg* (the short rainy season) at the plot level. However, many plots have two crops grown on them annually (one during each of the *Meher* and *Belg* seasons).

The farming system in the survey sites is very traditional with plough and yolk (animals' draught power). Labor is the major input in the production process during land preparation, planting, and post harvest processing. Labor inputs were disaggregated as adult male's labor, adult female's labor, and children's labor. This approach of collecting data (both inputs and outputs) at different stages of production and at different levels of disaggregation should reduce cognitive burden on the side of the respondents, and increase the likelihood of retrieving a better retrospective data. The three forms of labor were aggregated as one labor input using adult equivalents. We employed the standard conversion factor in the literature on developing countries where an adult female and children labor are converted into adult male labor equivalent at 0.8 and 0.3 rates, respectively.

Monthly rainfall and temperature data were collected from all the meteorological stations in the country. Then, the *Thin Plate Spline* method of spatial interpolation was used to impute the household specific rainfall and temperature values using latitude, longitude, and elevation information of each household. By definition, *Thin Plate Spline* is a physically based two-dimensional interpolation scheme for arbitrarily spaced tabulated data. The Spline surface represents a thin metal sheet that is constrained not to move at the grid points, which ensures that the generated rainfall and temperature data at the weather stations are exactly the same as data at the weather station sites that were used for the interpolation. In our case, the rainfall and temperature data at the weather stations are reproduced by the interpolation for those stations, which ensures the credibility of the method (see Wahba 1990). This method is one of the most commonly used to create spatial climate data sets. Its strengths are that it is readily available, relatively easy to apply, and it accounts for spatially varying elevation relationships. However, it only simulates elevation relationship, and it has difficulty handling very sharp spatial gradients. This is typical of coastal areas. Given that our area of the study is characterized by significant terrain features, and no climatically important coastlines, the choice of the *Thin Spline method* is reasonable (for more details on the properties of this method in comparison to the other methods, see Daly 2006).

Finally, although a total of forty-eight annual crops were grown in the basin, the first five major annual crops (teff, maize, wheat, barley, and beans) cover 65% of the plots. These are also the crops that are the cornerstone of the local diet. We limit the estimation to these primary crops. The final sample includes twenty *woredas*, 941 farm households (i.e., on average about forty-seven farm households per *woreda*), and 2,807 plots (i.e., on average about three plots per farm household). The scale of the analysis is at the plot level. The basic descriptive statistics are presented in table 1, and the definition of the variables in table A1 of the appendix.

Modeling Adaptation to Climate Change

The climate change adaptation decision and its implications in terms of food productivity (our metric of food security) can be modeled in the setting of a two-stage framework. In the first stage, we use a selection model for climate change adaptation where a representative risk adverse farm household chooses to implement climate change adaptation strategies if it generates net benefits.[5] Let A^* be the latent variable that captures the expected benefits from the adaptation choice with respect to not adapting. We specify the latent variable as

$$(1) \qquad A_i^* = \mathbf{Z_i}\boldsymbol{\alpha} + \eta_i \text{ with } A_i = \begin{cases} 1 & \textit{if } A_i^* > 0 \\ 0 & \textit{otherwise}, \end{cases}$$

that is farm household i will choose to adapt ($A_i = 1$), through the implementation of some strategies in response to long term changes in mean temperature and rainfall, if $A^* > 0$, and 0 otherwise.

The vector $\mathbf{Z}$ represents variables that affect the expected benefits of adaptation. These factors can be classified in different groups. First, we consider the characteristics of the operating farm (e.g., soil fertility, erosion). For instance, farms characterized by more fertile soil might be less affected by climate change and therefore relatively less likely to implement adaptation strategies. Then, current climatic factors (e.g., rainfall, temperature) as well as the experience of previous extreme events such as droughts and floods (in the last five years) can also play a role in determining the probability of adaptation. It is also important to address the role of access to credit. Households that have limited access to credit can have less

[5] A more comprehensive model of climate change adaptation is provided by Mendelsohn (2000).

Table 1. Descriptive Statistics

Variable name	Total sample Mean	Total sample Std. Dev.	Farm households that adapted Mean	Farm households that adapted Std. Dev.	Farm households that did not adapt Mean	Farm households that did not adapt Std. Dev.
Dependent variables						
adaptation	0.689	0.463	1.000	0.000	0.000	0.000
quantity produced per hectare	1,049.923	1,197.687	1,133.880	1,355.747	863.524	699.301
Explanatory variables						
Climatic factors						
Belg rainfall	322.881	160.644	307.921	150.277	356.095	177.186
Meher rainfall	1,111.162	295.047	1,145.948	285.157	1,033.931	302.059
average temperature	17.736	2.032	17.160	1.771	19.014	1.992
Soil characteristics						
highly fertile	0.280	0.449	0.257	0.437	0.331	0.471
infertile	0.158	0.365	0.172	0.377	0.128	0.335
no erosion	0.484	0.500	0.472	0.499	0.510	0.500
severe erosion	0.104	0.305	0.114	0.318	0.081	0.274
Assets						
machinery	0.019	0.136	0.024	0.153	0.007	0.084
animals	0.874	0.332	0.887	0.317	0.842	0.365
Inputs						
labor	100.994	121.268	105.867	133.409	90.176	87.657
seeds	114.905	148.650	125.672	163.896	91.001	103.473
fertilizers	60.609	176.767	61.996	177.867	57.530	174.362
manure	198.148	831.347	254.560	951.670	72.758	438.123
Farmer head and farm household characteristics						
literacy	0.489	0.500	0.524	0.500	0.412	0.492
male	0.926	0.263	0.932	0.252	0.912	0.284
married	0.927	0.261	0.930	0.256	0.920	0.272
age	45.717	12.550	46.239	11.926	44.556	13.770
household size	6.597	2.190	6.760	2.138	6.234	2.260
off-farm job	0.250	0.433	0.285	0.452	0.170	0.376
relatives	16.464	43.630	19.534	51.284	9.457	13.259
access to credit	0.260	0.439	0.308	0.462	0.155	0.362
gold	0.377	0.485	0.453	0.498	0.206	0.405
flood experience	0.172	0.378	0.216	0.412	0.075	0.263
drought experience	0.443	0.497	0.565	0.496	0.172	0.378
Information sources						
government extension	0.609	0.488	0.761	0.426	0.269	0.444
farmer-to-farmer extension	0.516	0.500	0.660	0.474	0.196	0.397
radio information	0.307	0.461	0.382	0.486	0.139	0.346
neighborhood information	0.316	0.465	0.320	0.467	0.306	0.461
climate information	0.422	0.494	0.563	0.496	0.110	0.313
Sample size	2,807		1,936		871	

Note: The sample size refers to the total number of plots. The final total sample includes 20 *woredas*, 941 farm households, and 2,807 plots.

capital available to be invested in the implementation of more costly adaptation strategies (e.g., soil conservation measures). Farmers must have access to information about farming practices before they can consider adopting them. Since extension services are one important means for farmers to gain information on this, access to extension (both government and farmer-to-farmer) can be used as a measure of access to information. Particularly relevant in this setting is that farmers received information on climate. Farmer head and farm household's characteristics (e.g., age, gender, education, marital status, if the farmer head has an off-farm job, farm household size), and the presence of assets (e.g., machinery, animals) may in principle also affect the probability of adaptation. Experience is approximated by age and education.

In the second stage, we model the effect of adaptation on food productivity via a representation of the production technology. We explored different functional forms. We present the most robust: a quadratic specification. It has been argued that single output production functions do not capture the possibility of switching crops, and therefore the estimated impact of climatic variables on production is biased (Mendelsohn et al. 1994). This can be particularly relevant when we look at a fairly specialized agriculture such as in the United States. However, in Ethiopia agriculture is characterised by high crop diversification. Each farm grows a relatively large number of different cereal crops. Considering the total yields of cereal crops implicitly deals with these alternatives.

The simplest approach to examine the impact of adaptation to climate change on farm households' food productivity would be to include in the food productivity equation a dummy variable equal to 1 if the farm-household adapted to climate change, and then, to apply ordinary least squares (OLS). This approach, however, might yield biased estimates because it assumes that adaptation to climate change is exogenously determined while it is potentially endogenous. The decision to adapt or not to climate change is voluntary and may be based on individual self-selection. Farmers that adapted may have systematically different characteristics from the farmers that did not adapt, and they may have decided to adapt based on expected benefits. Unobservable characteristics of farmers and their farm may affect both the adaptation decision and food productivity, resulting in inconsistent estimates of the effect of adaptation on food security. For example, if only the most skilled or motivated farmers choose to adapt and we fail to control for skills, then we will incur upward bias.

We account for the endogeneity of the adaptation decision by estimating a simultaneous equations model of climate change adaptation and food productivity with endogenous switching by full information maximum likelihood (FIML). For the model to be identified it is important to use as exclusion restrictions, thus as selection instruments, not only those automatically generated by the nonlinearity of the selection model of adaptation (1) but also other variables that directly affect the selection variable but not the outcome variable.

In our case study, we use as selection instruments in the productivity function the variables related to the information sources (e.g., government extension, farmer-to-farmer extension, information from radio, neighborhood and, if received, information in particular on climate). We establish the admissibility of these instruments by performing a simple falsification test: if a variable is a valid selection instrument, it will affect the adaptation decision but it will not affect the quantity produced per hectare among farm households that did not adapt.[6] Table A2 of the appendix shows that the information sources can be considered as valid selection instruments: they are jointly statistically significant drivers of the decision to adapt or not to climate change (Model 1, $\chi^2 = 71.93$; $p = 0.00$) but not of the quantity produced per hectare by the farm households that did not adapt (Model 2, F-stat. $= 1.20, p = 0.35$).

To account for selection biases we adopt an endogenous switching regression model of food productivity where farmers face two regimes (1) to adapt, and (2) not to adapt defined as follows:

$$\text{(2}a\text{)} \quad \text{Regime 1: } y_{1i} = \mathbf{X_{1i}\beta_1} + \varepsilon_{1i} \quad \textit{if } A_i = 1$$

$$\text{(2}b\text{)} \quad \text{Regime 2: } y_{2i} = \mathbf{X_{2i}\beta_2} + \varepsilon_{2i} \quad \textit{if } A_i = 0$$

where y_i is the quantity produced per hectare in regimes 1 and 2, and $\mathbf{X_i}$ represents a vector of inputs (e.g., seeds, fertilizers, manure, labor), and of the farmer head's and the farm household's characteristics, soil's characteristics, assets, and the climatic factors included in $\mathbf{Z}$.

Finally, the error terms in equations (1), (2a), and (2b) are assumed to have a trivariate normal distribution, with zero mean and covariance matrix $\mathbf{\Sigma}$, i.e., $(\eta, \varepsilon_1, \varepsilon_2)' \sim N(\mathbf{0}, \mathbf{\Sigma})$

$$\text{with } \mathbf{\Sigma} = \begin{bmatrix} \sigma_\eta^2 & \sigma_{\eta 1} & \sigma_{\eta 2} \\ \sigma_{1\eta} & \sigma_1^2 & . \\ \sigma_{2\eta} & . & \sigma_2^2 \end{bmatrix}$$

where σ_η^2 is the variance of the error term in the selection equation (1), which can be assumed to be equal to 1, since the coefficients are estimable only up to a scale factor (Maddala 1983, p. 223), σ_1^2 and σ_2^2 are the variances of the

[6] We thank an anonymous reviewer for this useful suggestion.

error terms in the productivity functions (2*a*) and (2*b*), and $\sigma_{1\eta}$ and $\sigma_{2\eta}$ represent the covariance of η_i and ε_{1i} and ε_{2i}.[7] Since y_{1i} and y_{2i} are not observed simultaneously the covariance between ε_{1i} and ε_{2i} is not defined (reported as dots in the covariance matrix $\boldsymbol{\Sigma}$, Maddala 1983, p. 224). An important implication of the error structure is that because the error term of the selection equation (1) η_i is correlated with the error terms of the productivity functions (2*a*) and (2*b*) (ε_{1i} and ε_{2i}), the expected values of ε_{1i} and ε_{2i} conditional on the sample selection are nonzero:

$$E[\varepsilon_{1i}|A_i = 1] = \sigma_{1\eta}\frac{\phi(\mathbf{Z_i}\boldsymbol{\alpha})}{\Phi(\mathbf{Z_i}\boldsymbol{\alpha})} = \sigma_{1\eta}\lambda_{1i}, \text{ and}$$

$$E[\varepsilon_{2i}|A_i = 0] = -\sigma_{2\eta}\frac{\phi(\mathbf{Z_i}\boldsymbol{\alpha})}{1-\Phi(\mathbf{Z_i}\boldsymbol{\alpha})} = \sigma_{2\eta}\lambda_{2i},$$

where $\phi(.)$ is the standard normal probability density function, $\Phi(.)$ the standard normal cumulative density function, and $\lambda_{1i} = \frac{\phi(\mathbf{Z_i}\boldsymbol{\alpha})}{\Phi(\mathbf{Z_i}\boldsymbol{\alpha})}$, and $\lambda_{2i} = -\frac{\phi(\mathbf{Z_i}\boldsymbol{\alpha})}{1-\Phi(\mathbf{Z_i}\boldsymbol{\alpha})}$. If the estimated covariances $\hat{\sigma}_{1\eta}$ and $\hat{\sigma}_{2\eta}$ are statistically significant, then the decision to adapt and the quantity produced per hectare are correlated, that is we find evidence of endogenous switching and reject the null hypothesis of the absence of sample selectivity bias. This model is defined as a "switching regression model with endogenous switching" (Maddala and Nelson 1975).

An efficient method to estimate endogenous switching regression models is full information maximum likelihood estimation (Lee and Trost 1978).[8] The logarithmic likelihood function given the previous assumptions regarding the distribution of the error terms is

$$\text{(3)}\quad \ln L_i = \sum_{i=1}^{N} A_i\left[\ln\phi\left(\frac{\varepsilon_{1i}}{\sigma_1}\right) - \ln\sigma_1 + \ln\Phi(\theta_{1i})\right] + (1-A_i)\left[\ln\phi\left(\frac{\varepsilon_{2i}}{\sigma_2}\right) - \ln\sigma_2 + \ln(1-\Phi(\theta_{2i}))\right]$$

where $\theta_{ji} = \frac{(\mathbf{Z_i}\boldsymbol{\alpha} + \rho_j\varepsilon_{ji}/\sigma_j)}{\sqrt{1-\rho_j^2}}$, $j = 1, 2$, with ρ_j denoting the correlation coefficient between the error term η_i of the selection equation (1) and the error term ε_{ji} of equations (2*a*) and (2*b*), respectively.[9]

Conditional Expectations, Treatment, and Heterogeneity Effects

The endogenous switching regression model can be used to compare the expected food productivity of the farm households that adapted (a) with respect to the farm households that did not adapt (b), and to investigate the expected food productivity in the counterfactual hypothetical cases (c) that the adapted farm households did not adapt, and (d) that the nonadapted farm household adapted. The conditional expectations for food productivity in the four cases are presented in table 2 and defined as follows:

$$\text{(4a)}\quad E(y_{1i}|A_i = 1) = \mathbf{X_{1i}}\boldsymbol{\beta_1} + \sigma_{1\eta}\lambda_{1i}$$

$$\text{(4b)}\quad E(y_{2i}|A_i = 0) = \mathbf{X_{2i}}\boldsymbol{\beta_2} + \sigma_{2\eta}\lambda_{2i}$$

$$\text{(4c)}\quad E(y_{2i}|A_i = 1) = \mathbf{X_{1i}}\boldsymbol{\beta_2} + \sigma_{2\eta}\lambda_{1i}$$

$$\text{(4d)}\quad E(y_{1i}|A_i = 0) = \mathbf{X_{2i}}\boldsymbol{\beta_1} + \sigma_{1\eta}\lambda_{2i}.$$

Cases (a) and (b) along the diagonal of table 2 represent the actual expectations observed in the sample. Cases (c) and (d) represent the counterfactual expected outcomes.

[7] For notational simplicity, the covariance matrix $\boldsymbol{\Sigma}$ does not reflect the clustering that we will implement in the empirical analysis. In addition, as an anonymous reviewer emphasized, constraining the variance term in a single equation to equal one is not the same as deriving the proper form of the posterior or even the sampling distribution of the cross-equation correlation matrix. However, the same criticism could be levelled at previously published, respectable empirical work (see, e.g., Maddala 1983 or Bellemare and Barrett 2006). This problem—the one of constraining a single quantity in an inverted-Wishart-distributed covariance matrix—is important in multinomial settings and has generated some interest in Bayesian circles (Linnardakis and Dellaportas 2003; Nobile 2000; Smith and Hocking 1972).

[8] An alternative estimation method is the two-step procedure (see Maddala 1983, p. 224 for details). However, this method is less efficient than FIML, it requires some adjustments to derive consistent standard errors (Maddala 1983, p. 225), and it poorly performs in cases of high multicollinearity between the covariates of the selection equation (1) and the covariates of the food productivity equations (2*a*) and (2*b*) (Hartman 1991; Nawata 1994; Nelson 1984).

[9] We also addressed the issue of possible technical inefficiency. In this situation one can expect the expected value of the error terms to be negative. We estimated a stochastic production frontier, and we found no evidence that technical inefficiency is stochastic. Therefore, technical inefficiency seems not to affect the empirical analysis. Results are available from the authors upon request.

Table 2. Conditional Expectations, Treatment, and Heterogeneity Effects

Subsamples	Decision stage: To adapt	Decision stage: Not to adapt	Treatment effects
Farm households that adapted	(a) $E(y_{1i} \mid A_i = 1)$	(c) $E(y_{2i} \mid A_i = 1)$	TT
Farm households that did not adapt	(d) $E(y_{1i} \mid A_i = 0)$	(b) $E(y_{2i} \mid A_i = 0)$	TU
Heterogeneity effects	BH_1	BH_2	TH

Note: (a) and (b) represent observed expected production quantities per hectare; (c) and (d) represent counterfactual expected production quantities per hectare.
$A_i = 1$ if farm households adapted to climate change; $A_i = 0$ if farm households did not adapt;
Y_{1i}: quantity produced if farm households adapted;
Y_{2i}: quantity produced if farm households did not adapt;
TT: the effect of the treatment (i.e., adaptation) on the treated (i.e., farm households that adapted);
TU: the effect of the treatment (i.e., adaptation) on the untreated (i.e., farm households that did not adapt);
BH_i: the effect of base heterogeneity for farm households that adapted ($i = 1$), and did not adapt ($i = 2$);
TH = (TT - TU), i.e., transitional heterogeneity.

In addition, following Heckman et al. (2001), we calculate the effect of the treatment "to adapt" on the treated (TT) as the difference between (a) and (c),

$$TT = E(y_{1i} \mid A_i = 1) - E(y_{2i} \mid A_i = 1) = \mathbf{X_{1i}}(\boldsymbol{\beta_1} - \boldsymbol{\beta_2}) + (\sigma_{1\eta} - \sigma_{2\eta})\lambda_{1i} \tag{5}$$

which represents the effect of climate change adaptation on the food productivity of the farm households that actually adapted to climate change. Similarly, we calculate the effect of the treatment on the untreated (TU) for the farm households that actually did not adapt to climate change as the difference between (d) and (b),

$$TU = E(y_{1i} \mid A_i = 0) - E(y_{2i} \mid A_i = 0) = \mathbf{X_{2i}}(\boldsymbol{\beta_1} - \boldsymbol{\beta_2}) + (\sigma_{1\eta} - \sigma_{2\eta})\lambda_{2i}. \tag{6}$$

We can use the expected outcomes described in equations (4*a*)–(4*d*) to calculate also the heterogeneity effects. For example, farm households that adapted may have produced more than farm households that did not adapt regardless of the fact that they decided to adapt but because of unobservable characteristics such as their skills. We follow Carter and Milon (2005) and define as "the effect of base heterogeneity" for the group of farm households that decided to adapt as the difference between (a) and (d),

$$BH_1 = E(y_{1i} \mid A_i = 1) - E(y_{1i} \mid A_i = 0) = (\mathbf{X_{1i}} - \mathbf{X_{2i}})\boldsymbol{\beta_{1i}} + \sigma_{1\eta}(\lambda_{1i} - \lambda_{2i}). \tag{7}$$

Similarly for the group of farm households that decided not to adapt, "the effect of base heterogeneity" is the difference between (c) and (b),

$$BH_2 = E(y_{2i} \mid A_i = 1) - E(y_{2i} \mid A_i = 0) = (\mathbf{X_{1i}} - \mathbf{X_{2i}})\boldsymbol{\beta_{2i}} + \sigma_{2\eta}(\lambda_{1i} - \lambda_{2i}). \tag{8}$$

Finally, we investigate the "transitional heterogeneity" (TH), that is whether the effect of adapting to climate change is larger or smaller for farm households that actually adapted to climate change or for farm households that actually did not adapt in the counterfactual case that they did adapt, that is the difference between equations (5) and (6) (i.e., TT and TU).

Results

Table 3 reports the estimates of the endogenous switching regression model estimated by full information maximum likelihood with clustered standard errors at the *woreda* level.[10] The first column presents the estimation by OLS of the food productivity function with no switching and with a dummy variable equal to 1 if the farm household decided to adapt to climate change, 0 otherwise. The second, third and fourth columns present, respectively, the estimated coefficients of selection equation (1) on adapting or not to climate change, and of the food productivity functions (2*a*) and (2*b*) for farm households that did and did not adapt to climate change.

The results of the estimation of equation (1) suggest that the main drivers of farm households' decision to adopt some strategies in

[10] We use the "movestay" command of STATA to estimate the endogenous switching regression model by FIML (Lokshin and Sajaia 2004).

Table 3. Parameters Estimates of Climate Change Adaptation and Food Productivity Equations

	(1)	(2)	(3)	(4)
		Endogenous switching regression[a]		
Model	OLS		Adaptation = 1 (farm households that adapted)	Adaptation = 0 (farm households that did not adapt)
Dependent variable	Quantity produced per hectare	Adaptation 1/0	Quantity produced per hectare	Quantity produced per hectare
Adaptation 1/0	141.157			
	(126.077)			
Climatic factors				
Belg rainfall	−1.239	0.001	−2.275	−0.091
	(1.368)	(0.004)	(2.012)	(0.986)
squared Belg rainfall/1000	1.176	−0.004	3.155	−1.067
	(1.847)	(0.005)	(2.896)	(1.748)
Meher rainfall	0.374	0.003	−1.458	1.666*
	(1.385)	(0.003)	(1.531)	(0.919)
squared Meher rainfall/1000	−0.095	−0.001	0.695	−0.619*
	(0.594)	(0.001)	(0.655)	(0.325)
average temperature	142.866	−0.944	561.815	−166.567
	(266.694)	(0.770)	(355.619)	(334.002)
squared average temperature	−4.375	0.020	−15.608	4.502
	(7.351)	(0.020)	(9.853)	(8.201)
Soil characteristics				
highly fertile	158.918**	−0.211**	204.036**	70.425
	(71.973)	(0.099)	(90.977)	(64.179)
infertile	−80.002	−0.011	−139.217**	−6.276
	(53.328)	(0.118)	(56.297)	(58.533)
no erosion	9.312	0.126	35.644	−15.116
	(64.942)	(0.135)	(86.769)	(52.325)
severe erosion	28.536	−0.025	67.477	−35.219
	(106.578)	(0.099)	(130.523)	(90.780)
Assets				
machinery	−226.165	0.839	−254.164	−157.032
	(131.425)	(0.636)	(170.539)	(102.745)
animals	179.698**	0.009	187.609*	153.186**
	(82.289)	(0.240)	(104.578)	(71.774)
Inputs				
labor	3.088***		3.357***	3.731***
	(0.821)		(1.088)	(0.615)
squared labor /100	−0.124**		−0.131*	−0.409***
	(0.055)		(0.073)	(0.076)
seeds	1.900**		2.410***	−0.020
	(0.803)		(0.940)	(0.735)
squared seeds /100	0.073**		0.050	0.352**
	(0.033)		(0.039)	(0.145)
fertilizers	0.843**		0.644*	0.975***
	(0.331)		(0.381)	(0.326)
squared fertilizers/100	−0.014		−0.005	−0.026***
	(0.009)		(0.009)	(0.008)
manure	0.295***		0.278***	0.036
	(0.073)		(0.072)	(0.162)
squared manure /100	−0.003***		−0.003	0.003
	(0.001)		(0.001)	(0.003)

(*Continued*)

Table 3. Continued

	(1)	(2)	(3)	(4)
		Endogenous switching regression[a]		
Model	OLS		Adaptation = 1 (farm households that adapted)	Adaptation = 0 (farm households that did not adapt)
Dependent variable	Quantity produced per hectare	Adaptation 1/0	Quantity produced per hectare	Quantity produced per hectare
Farmer head and farm household characteristics				
literacy	−72.337	0.092	−60.929	−109.925*
	(57.625)	(0.120)	(76.278)	(60.081)
male	229.001*	0.149	147.881	390.360***
	(114.000)	(0.288)	(161.671)	(61.563)
married	−79.523	−0.235	68.143	−380.746***
	(106.112)	(0.359)	(120.501)	(97.915)
age	−2.982	0.007	−3.324*	−3.201
	(1.801)	(0.004)	(2.000)	(2.080)
household size	−9.561	0.052*	−8.592	1.375
	(13.514)	(0.030)	(17.111)	(9.615)
off-farm job	187.408**	0.223	180.602*	16.133
	(82.762)	(0.143)	(95.119)	(73.289)
relatives	0.196	0.004	0.316	−0.492
	(0.281)	(0.004)	(0.277)	(2.293)
access to credit	−96.900	0.246*	−55.334	−275.524***
	(77.491)	(0.142)	(102.894)	(56.882)
gold	−128.807	0.050	−116.193	−26.010
	(83.427)	(0.170)	(95.757)	(39.374)
flood experience	−51.911	0.107	−40.965	161.961
	(80.824)	(0.165)	(88.327)	(160.036)
drought experience	−94.552	0.137	−153.134*	−84.851
	(80.366)	(0.226)	(78.900)	(136.433)
Information sources				
government extension		0.457***		
		(0.109)		
farmer-to-farmer extension		0.404***		
		(0.144)		
radio information		0.325		
		(0.215)		
neighborhood information		−0.127		
		(0.150)		
climate information		0.465**		
		(0.213)		
constant	−843.590	7.563	−3,578.829	1,178.673
	(2,046.697)	(7.454)	(2,798.254)	(3,332.793)
σ_i			1145.401***	583.255***
			(134.830)	(67.989)
ρ_j			−0.074	−0.196
			(0.194)	(0.271)

Note: [a] Estimation by full information maximum likelihood at the plot level.
Sample size: 2,807 plots. Robust standard errors clustered at the *woreda* level in parentheses. σ_i denotes the square-root of the variance of the error terms ε_{ji} in the outcome equations (2*a*) and (2*b*), respectively; ρ_j denotes the correlation coefficient between the error term η_i of the selection equation (1) and the error term ε_{ji} of the outcome equations (2*a*) and (2*b*), respectively. *Significant at the 10% level; **Significant at the 5% level; ***Significant at the 1% level.

response to long term changes in mean temperature and rainfall are represented by the provision of climate information both from formal and informal institutions, and access to credit (table 3, column (2)). Farm households with access to credit are found to be more likely to adapt to climate change. The role of information also seems very important. We find that farmers that were informed about the climate are more likely to adapt. Moreover, information provided by extension services also plays an important role in determining farmers' decision to adapt. Both formal agricultural extension through government extension officers and farmer-to-farmer extension increase the probability of adaptation. The results on access to credit and information highlight that farmers may need both information on the adaptation strategies and financial resources to implement them. To further investigate the relative importance of these two variables we restrict the analysis to the sub sample of credit constrained farm households. We find that information provision still has a strong significant positive effect on the probability of adapting (table A3 of the appendix). This may indicate that lack of access to extension services may be the most crucial obstacle to adaptation.

We also find that farm households with highly fertile soils are less likely to implement some adaptation strategies. Current climatic variables seem to play no role in determining the probability of adaptation. Rainfall in the long rainy season displays an *inverted U*-shape behavior. A similar pattern is identified when we look at the rainfall level during the *Belg* short rainy season. However, the coefficients are not statistically significant since adaptation is highly clustered at the *woreda* level.

We now turn on the productive implications of adaptation. The simplest approach to investigate the effect of adaptation on food productivity consists in estimating an OLS model of food productivity that includes a dummy variable equal to 1 if the farm household adapted, 0 otherwise (table 3, column (1)). This approach would lead us to conclude that there is no difference in the quantity produced per hectare by farm households that adapted with respect to the quantity produced by farm households that did not adapt (the coefficient of the dummy variable *adaptation* is positive but insignificant). This approach, however, assumes that adaptation to climate change is exogenously determined while it is a potentially endogenous variable. The estimation via OLS would yield biased and inconsistent estimates. In addition, OLS estimates do not explicitly account for potential structural differences between the productivity function of farm households that adapted to climate change and the productivity function of farm households that did not adapt.

The estimates presented in the last two columns of table 3 account for the endogenous switching in the food productivity function. Both the estimated coefficients of the correlation terms ρ_j are not significantly different from zero (table 3, bottom row). Although we could not have known it a priori, this implies that the hypothesis of absence of sample selectivity bias may not be rejected.

However, the differences in the coefficients of the food productivity equation between the farm households that adapted and those that did not adapt illustrate the presence of heterogeneity in the sample (table 3, columns (3) and (4)). The food productivity function of farm households that adapted to climate change is significantly different (at the 1% statistical level) from the productivity function of farm households that did not adapt. Consistent with predictions of economic theory, inputs such as seeds, fertilizers, manure and labor are significantly associated with an increase in the quantity produced per hectare by the farm households that adapted to climate change. However, mainly labor and fertilizers seem to significantly affect the food productivity of the farm households that did not adapt.[11]

Another interesting difference between the farm households that did and those that did not adapt concerns the effect of temperature and rainfall on the quantity produced per hectare. Differently from the existing literature, we analyze the impact of climatic variables for the two different groups. When we distinguish between farm households that adapted versus farm households that did not adapt and we control for the different rainy seasons, we can unearth very interesting and distinct patterns. We find that while mean temperature and rainfall do not affect the productivity of farm households that adapted to climate change, the relationship between productivity and mean rainfall in the *Meher* season is *inverted U*-shaped for

[11] We also investigate the potential endogeneity of access to credit in the productivity function and the associated negative sign. We reject the endogeneity at the 1% statistical level. We use as instrument the average proportion of farm households with access to credit in the *woreda*. This instrument is a strong predictor of access to credit (at the 1% statistical level). The negative sign associated with access to credit can be explained by the fact that the farm households that access to credit are those with a productivity level lower than those that do not access to credit.

Table 4. Average Expected Production per Hectare; Treatment and Heterogeneity Effects

	Decision stage		
Sub-samples	To adapt	Not to adapt	Treatment effects
Farm households that adapted	(a) 1,133.895 (16.507)	(c) 952.629 (21.040)	TT = 181.266*** (14.213)
Farm households that did not adapt	(d) 1,161.785 (18.384)	(b) 862.838 (13.343)	TU = 298.947*** (12.981)
Heterogeneity effects	$BH_1 = -27.890$ (27.527)	$BH_2 = 89.791$*** (32.623)	TH = −117.681*** (22.910)

See note of table 2. Standard errors in parentheses. ***Significant at the 1% level.

farm households that did not adapt to climate change. This seems to indicate that the implementation of the adaptation strategies successfully made the farm households that adapted more resilient to the most important rainfall season, *Meher*.

Table 4 presents the expected quantity produced per hectare under actual and counterfactual conditions. Cells (a) and (b) represent the expected quantity produced per hectare observed in the sample. The expected quantity produced per hectare by farm households that adapted is about 1,134 kg, while it is about 863 kg for the group of farm households that did not adapt. This simple comparison, however, can be misleading and drive the researcher to conclude that on average the farm households that adapted produced about 271 kg (that is 31%) more than the farm households that did not adapt.

The last column of table 4 presents the treatment effects of adaptation on food productivity. In the counterfactual case (c), farm households who actually adapted would have produced about 181 kg (that is about 20%) less if they did not adapt. In the counterfactual case (d) that farm households that did not adapt adapted, they would have produced about 299 kg (that is about 35%) more if they had adapted. These results imply that adaptation to climate change significantly increases food productivity; however, the transitional heterogeneity effect is negative, that is, the effect is significantly smaller for the farm households that actually did adapt relative to those that did not adapt.

In addition, the last row of table 4, which adjusts for the potential heterogeneity in the sample, shows that farm households who actually adapted would have produced significantly more than the farm households that did not adapt in the counterfactual case (c). This highlights that there are some important sources of heterogeneity that makes the adapters "better producers" than the nonadapters irrespective to the issue of climate change. Nevertheless the farm households who adapted are still better off adapting than not adapting. Finally, in the counterfactual case (d) that the nonadapted farm households had adapted, they would have produced the same as the farm household that actually adapted.

Conclusions

The objectives of this paper were to analyse the driving forces behind farm households' decision to adapt to climate change, and to investigate the productive implications of this decision. We used a unique database, where climatic information was disaggregated per season and available at the farm level to estimate a simultaneous equations model with endogenous switching to account for unobservable factors that influence food productivity and the decision to adapt.

The analysis of the determinants of adaptation highlighted very interesting results. Both access to credit and information provision have a positive effect on the probability of adaptation. Developing credit markets allow farm households to make important investments (e.g., soil conservation strategies) that can support food productivity. Information on climate change and extension services also play an important role in determining farm households' decisions to adapt. Both formal agricultural extension through government officers and farmer-to-farmer extension increase the probability of adaptation. In addition, rainfall displays an *inverted U*-shape behavior in the *Meher* season among farm households that did not adapt while it does not affect the productivity of farm households that adapted. This result may indicate that the adaptation made the farm households that adapted more resilient during the most important rainfall season, *Meher*.

Finally, we can draw three main conclusions from the results of this study on the effects of climate change adaptation on food security. First, the group of farm households that did adapt has systematically different characteristics than the group of farm households that did not adapt. These differences represent sources of variation between the two groups that the estimation of an OLS model including a dummy variable for adapting or not to climate change cannot take into account.

Second, adaptation to climate change increases food productivity. When we analyze this result for the two different groups of farm households, "adapters" and "non-adapters," interesting patterns emerge. Farm households who actually adapted tend to produce more than farm households that did not adapt in the counterfactual case that they did not adapt. Farm households belonging to the group of the "adapters" have some characteristics (e.g., unobserved skills) that would make them more food secure even without the implementation of the adaptation strategies. This might explain our third finding. Interestingly, we also found that the impact of adaptation on food productivity is smaller for the farm households that actually did adapt than for the farm households that did not adapt in the counterfactual case that they adapted. It seems, therefore, that while both groups of farm households would benefit from the implementation of adaptation strategies, the farm households that did not adapt would benefit the most from adaptation. This beneficial effect of adaptation is found to be large. If the farm households that did not adapt had adapted, they would have produced the same as the farm households that actually adapted. Therefore, adaptation strategies seem to be particularly important for the most vulnerable farm households, those who have already the least capability to produce food, by helping them to close the productive gap with the less vulnerable farm households.

These results are particularly important to design policies for effective adaptation strategies to cope with the potential impacts of climate change. Public policies can play an important role in helping farm households to adapt. The facilitation of the access to credit and the dissemination of climate change information and extension services are of paramount importance in determining the implementation of adaptation strategies, which could result in more food security for all farmers irrespective of their unobservable characteristics. The availability of information on climate change may raise farmers' awareness of the threats posed by the changing climatic conditions. Extension services provide an important source of information and education, for instance, on changing crops and specific soil conservation measures that can deliver food productivity gains. Access to the credit market can offer the necessary financial resources to adopt the technologies and acquire seeds of crops that are better suited to the changing climatic conditions.

In addition, to disentangle the relative importance of the information sources with respect to access to credit, we restricted the analysis to the sub-sample of credit-constrained farm households. The results reported in table A3 show that information sources are still strong significant drivers of the decision to adapt. This seems to indicate that lack of information may be a crucial obstacle to adaptation, and that information provision may be an effective policy to induce farm households to adapt. Future research is needed to better understand the behavioral dimension of the adaptation process. More research effort should also be allocated into the distinction of the role of different adaptation strategies and the identification of the most successful ones.

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Appendix

Table A1. Variables definition

Variable name	Definition
Dependent variables	
adaptation	dummy = 1 if the farm household adapted to climate change, 0 otherwise
quantity produced per hectare	quantity produced per hectare (kg)
Explanatory variables	
Climatic factors	
Belg rainfall	rainfall rate in *Belg*, short rain season (mm)
Meher rainfall	rainfall rate in *Meher*, long rain season (mm)
average temperature	average temperature (°C)
Soil characteristics	
high fertility	dummy = 1 if the soil has a high level of fertility, 0 otherwise
infertile	dummy = 1 if the soil is infertile, 0 otherwise
no erosion	dummy = 1 if the soil has no erosion, 0 otherwise
severe erosion	dummy = 1 if the soil has severe erosion, 0 otherwise
Assets	
machinery	dummy = 1 if machineries are used, 0 otherwise
animals	dummy = 1 if farm animal power is used, 0 otherwise
Inputs	
labor	labor use per hectare (adult days)
seeds	seeds use per hectare (kg)
fertilizers	fertilizers use per hectare (kg)
manure	manure use per hectare (kg)
Farmer head and farm household characteristics	
literacy	dummy = 1 if the household head is literate, 0 otherwise
male	dummy = 1 if the household head is male, 0 otherwise
married	dummy = 1 if the household head is married, 0 otherwise
age	age of the household head
household size	household size
off-farm job	dummy = 1 if the household head took an off-farm job, 0 otherwise
relatives	number of relatives in the *woreda*
access to credit	dummy = 1 if the farm household has access to formal credit, 0 otherwise
gold	dummy = 1 if the farm household has gold
flood experience	dummy = 1 if the farm household experienced a flood during the last 5 years
drought experience	dummy = 1 if the farm household experienced a drought during the last 5 years
Information sources	
government extension	dummy = 1 if the household head got information/advice from government extension workers, 0 otherwise
farmer-to-farmer extension	dummy = 1 if the household head got information/advice from farmer-to-farmer extension, 0 otherwise
radio information	dummy = 1 if the household head got information from radio, 0 otherwise
neighborhood information	dummy = 1 if the household head got information from the neighborhood, 0 otherwise
climate information	dummy = 1 if extension officers provided information on expected rainfall and temperature, 0 otherwise

Table A2. Parameter Estimates – Test on the Validity of the Selection Instruments

	Model 1	Model 2
	Adaptation 1/0	Quantity produced per hectare by farm households that did not adapt
Information sources		
government extension	0.455*** (0.114)	70.687 (80.121)
farmer-to-farmer extension	0.413*** (0.139)	4.693 (130.241)
radio information	0.327 (0.219)	5.163 (96.343)
neighborhood information	−0.099 (0.150)	−165.042* (85.374)
climate information	0.458** (0.224)	111.998 (138.529)
constant	7.648 (7.543)	2,596.864 (3,652.768)
Wald test on information sources	$\chi^2 = 72.97$***	F-stat. = 1.20
Sample size	2,807	872

Note: Model 1: Probit model (Pseudo $R^2 = 0.386$); Model 2: ordinary least squares ($R^2 = 0.331$). Estimation at the plot level. Standard errors clustered at the *woreda* level in parentheses. *Significant at the 10% level; **Significant at the 5% level; ***Significant at the 1% level. Parameters for all the other variables are not reported. The full table is available in the supplementary online appendix on the Oxford University Press website.

Table A3. Probit Model of Climate Change Adaptation for Credit Constrained Farm Households

	Parameter
Information sources	
government extension	0.480** (0.197)
farmer-to-farmer extension	0.266 (0.180)
radio information	0.249 (0.240)
neighborhood information	−0.140 (0.166)
climate information	0.660*** (0.246)
constant	6.956 (6.991)
Wald test on information sources	$\chi^2 = 42.59$***
Sample size	2,096

Note: Estimation at the plot level for sub-sample of farm households without access to credit. Standard errors clustered at the *woreda* level in parentheses. Pseudo $R^2 = 0.379$. **Significant at the 5% level; ***Significant at the 1% level. Parameters for all the other variables are not reported. The full table is available in the supplementary online appendix on the Oxford University Press website.